Real-Time Beam steering in mmWave with Reconfigurable Intelligent Meta-surfaces

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Real-Time Beam steering in mmWave with Reconfigurable Intelligent Meta-surfaces based on a Genetic Algorithm

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***Abstract*—The control logic of a reconfigurable meta-surface in mmWave is investigated in order to perform real-time beam steering in mobility contexts. When it is necessary to track an object or a person in movement, it is required to change the direction of the signal transmitted/reflected by the meta-surface. To do so, the meta-surface has to be reconfigured to modify the generated radiation pattern. Here a specific meta-surface, working around 78.5 GHz, is adopted, which consists of many unit-cells containing a diode to make its electromagnetic behaviour reconfigurable. In order to enable the system to adaptively compute the new coding schemes, namely to change the states of the meta-surface unit-cells, a machine-learning algorithm is adopted. In particular, we propose a Genetic Algorithm, integrate it in the architecture of our meta-surface and evaluate the performance. Results show that a good accuracy and a good convergence time are achieved for real-time beam steering functionality and the capacity of the system equipped with RIM (reconfigurable intelligent metasurface) is increased.**

***Index Terms*—Genetic Algorithm, Machine-Learning, beam-steering, meta-surface, mmWave.**

I. INTRODUCTION

Meta-surfaces are artificially engineered surfaces, given by the repetition of a unit cell (the meta-atom), that are able to manipulate incident electromagnetic waves in unconventional ways [1]. Reconfigurable meta-surfaces can perform different operations on the impinging electromagnetic waves according to the state of the switching components to satisfy the requests. When the conditions of the environment change or, more in general, the requirements for the meta-surfaces behaviour are modified, the new meta-surface configuration needs to be computed. Since the applications based on the reconfigurable meta-surfaces (e.g. beam steering) usually require a real-time response, it is not feasible to compute the new required configuration using conventional algorithms, neither, in the most of the applications, it is possible to compute the entire range of configurations before the working time because of their huge amount. Effects like molecular absorption, Doppler become more relevant at higher frequencies. For this reason, the adoption of high accurate machine learning algorithms to find the new states of the meta-atoms is much important.

These algorithms have been shown effective to optimize the coding matrix of a reconfigurable meta-surface in order to perform beam-steering or tuning its electromagnetic behaviour. Inside the work [3], deep learning techniques are adopted to code the programmable meta-surface for multi-beam steering. A deep convolutional neural network was built to compute the element codes given the requirement of the scattering patterns around 11.1 GHz. In [4], Genetic Algorithm is adopted in order to optimize the coding matrix of a reconfigurable meta-surface in such a way to tailor its scattering properties. In such a way, various functionalities, such as agile scattering, planar focusing, beam steering and beam forming, are obtained. Since the simulation time of Genetic Algorithm increases sharply with the size of the meta-surface, a 2 D IDFT is adopted too. In [5], a deep learning model is adopted for the mapping of meta-material physical structure parameters and the corresponding electromagnetic characteristic responses. More specifically, CNN (Convolutional Neural Network) is utilized to extract and learn the features of the model layer by layer. After training, given a specific coding structure, the end ports of the neural network may output S11 and S21 spectra directly. Machine-learning algorithms are used also to optimize MIMO performances. In [6], the authors developed an efficient beam-forming scheme for mmW MIMO using Genetic Algorithms. According to its simulated performances, the algorithm is suitable for delay-constrained systems. In [7], a methodology based on Genetic Algorithm for optimizing the data throughput of a MIMO system is discussed. More specifically, Genetic Algorithm is used to find the best antenna configuration which results in the highest data throughput.
Machine-learning algorithms are very suitable for V2I communications, where mobility is a great issue, because of their ability in providing fast responses. [8] proposes a situational awareness-aided beam training solution using machine learning in mmWave V2I communication. The optimal beam pair index is found by exploiting the locations and types of the receiver vehicle and its neighboring vehicles (situational awareness). In [9], the authors use reinforcement learning (RL) for beam-selection for 5G scenarios in V2I. RL is performed on a RSU (road-side unit) in order to

schedule a user in each time slot together with its beam pair. Despite their promising potential in wireless networks, very few works propose reconfigurable meta-surfaces operating at millimeter-wave frequencies [12].

In this work, we consider a meta-surface operating at mmWave that we have proposed in [14], presenting the suitable features in terms of tunability for beam steering applications. Moreover, we propose a Genetic Algorithm (GA) to integrate this meta-surface as computing unit and perform real-time beam steering functions in a mobile scenario. Even though we consider a limited set of parameters to characterize a radiation pattern, the Genetic Algorithm achieves high accuracy and reasonable convergence time.

The main contributions of this work can be summarized as follows:

- We integrate an intelligent logic based on a Genetic Algorithm in a meta-surface operating at mmWave. Even though we prove the approach in a specific meta-surface structure, the solution is generally valid and can be applied to whatever meta-surface;
- We assess the performance of the GA for beam-steering application in a wireless mobile context in terms of accuracy and convergence time;
- We evaluate the capacity of the communication system with and without meta-surface with GA.

The rest of the paper is organized as follows. In Section II, we present the different parts of the network. In Section III we describe the Genetic Algorithm proposed. In Section IV we evaluate the accuracy of the Genetic Algorithm integrated in the specific meta-surface operating at mmWave. In Section V the communication performances of the considered scenario are discussed. Finally, we conclude the paper in Section VI.

II. System model

We considered a scenario in which it is required to send information to a mobile receiver. In order to track the receiver position, a reconfigurable meta-surface with beam-steering capabilities has been adopted [14] (Fig. 1). Our meta-surface is tuned by the means of an FPGA (Field-Programmable Gate Array) fed by a unit logic, where our GA runs and compute in a real-time the new coding scheme of the meta-surface.

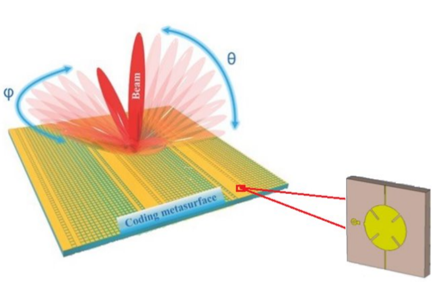

Fig. 1. 64 x 64 reconfigurable meta-surface consisting of four-leaf clover meta-atoms.

It has been designed to work in the 77 GHz bandwidth for applications in the automotive sector. But it can be extended also in all the other fields where it is necessary to track objects or people. The meta-surface has been designed in order to perform beam-steering of the impinging signal to a specific direction by tuning the state of each meta-atom. In order to obtain a meta-surface which can steer the direction of the reflected signal in a wide angular range, it is required that each meta-atom has reflective capabilities and that the phase of the signal reflected by each unit-cell can be switched between 0º and 180º. In order to reach this aim, the phase of the reflection coefficient is required to have a shift of 180º when the state of the diode is changed. For this reason, the four-leaf clover configuration has been chosen as unit-cell for this meta-surface (Fig. 2).

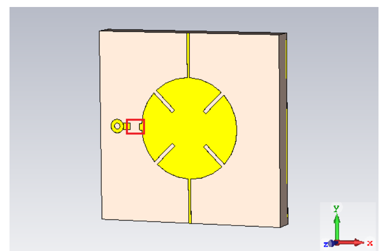

Fig. 2. Four-leaf clover meta-atom consisting of a metallic pattern, a dielectric substrate (Rogers RT5870) and a ground plane. The highlighted section represents a diode in ”off” state.

In the metallic pattern, a diode connected to a via hole is added in order to make the structure reconfigurable in terms of phase. By connecting the metallic pattern upon the substrate to the ground plane, the via hole creates a current path when the diode is on, thus producing a variation of phase. The substrate is made of Rogers RT5870 and it has a square shape with each side of length 2.679 mm and its thickness is 0.32 mm. The pattern upon the substrate is made of copper and it has been designed starting from a circumference, where four slots have been done. The via hole is connected to the slotted circumference through a diode, that for simplicity has been modeled with an open circuit when it is in ”off” state and as short circuit when it is in ”on” state. In the y direction two biasing lines have been added in preparation for the entire meta-surface made of the repetition of many identical unit-cells, where only the state of the diode can be modified. This unit-cell has been designed by adopting the ”trial and error” approach to obtain the desired features in terms of working frequencies and tuning capability of the phase. The simulation of the electromagnetic behaviour of the meta-atom has been performed on the simulation tool CST [13].

As mentioned before, in order to perform beam-steering, the single meta-atom is required to produce specific phase changes in the reflected signal. Fig. 3 shows the difference among the phases of the two reflection coefficients S_{11} (for ”on” state and for ”off” state). It is worth noticing that the higher difference between the two phase curves happens around 78 GHz. More precisely, the phase difference reaches 180º in 78.52 GHz. For more information on this structure, see [14].

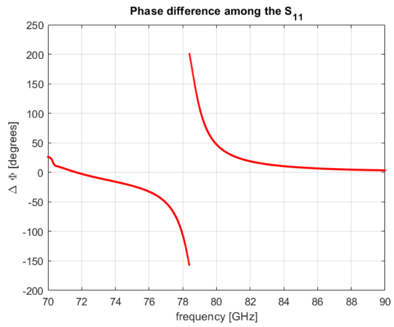

Fig. 3. Phase difference between the S_{11} in "off" and "on" state of the diode.

III. Genetic algorithm

In order to reconfigure each single meta-atom of the meta-surface presented in the previous section and to allow the meta-surface to perform beam steering, Genetic Algorithm has been chosen among all the machine learning algorithms.

This algorithm follows the process of natural selection where the fittest individuals are chosen for reproduction in order to produce offspring of the next generation. Genetic algorithms operate on string structures, like biological structures, which are evolving in time according to the rule of survival of the fittest by recombining and/or mutating them to try to satisfy a predefined objective function. Thus, in every generation, a new set of strings is created, using parts of the fittest members of the old set, that is superior than the old one from the point of view of the objective function [10].

A *population* is a set of possible phase configurations of the reconfigurable meta-surface that may satisfy the fitness function. Each configuration is an individual to whom the radiation pattern and upper mask (a matrix made of zeros and a single 1 in the position of the main beam) are associated. The gene is the state of a single meta-atom. In the *elite*, only the configurations with different direction of the main beam are listed, together with their corresponding radiation patterns and upper masks. We start with checking if the searched configuration that provides the upper mask of the wanted radiation pattern is found inside the *elite*. If not, the same procedure is repeated for the *population*. If the configuration is not present neither in the *population*, the number of individuals in the generation is increased by *cross-over* and *mutation*. The *cross-over* operation is the reproduction of new individuals that inherit part of the characteristics from two individuals, i.e. the parents. The *mutation* consists in flipping some genes of the individual with a low random probability. This operation is adopted in order to maintain diversity within the population and prevent premature convergence.

Then, the individuals who better respond to the fitness function are selected and, if they cannot provide the wanted upper mask, the reproduction step is repeated until the fitness function is satisfied or a certain number of generations are met.

GA can be seen as a method that explores a search space. Thanks to the operations of *cross-over* and *mutation*, the algorithm can explore very different areas of solutions moving away from local maxima, but the right direction for the search is maintained by the fitness function. An advantage of Genetic Algorithm is its low sensibility to the initial conditions with respect to traditional numerical techniques. A limit, instead, of this algorithm is that it can provide a local maximum as solution and sometimes it is not possible to understand if the solution is local or global.

The flow-chart of the adopted Genetic Algorithm is shown in Fig. 4. The wanted radiation pattern with the corresponding

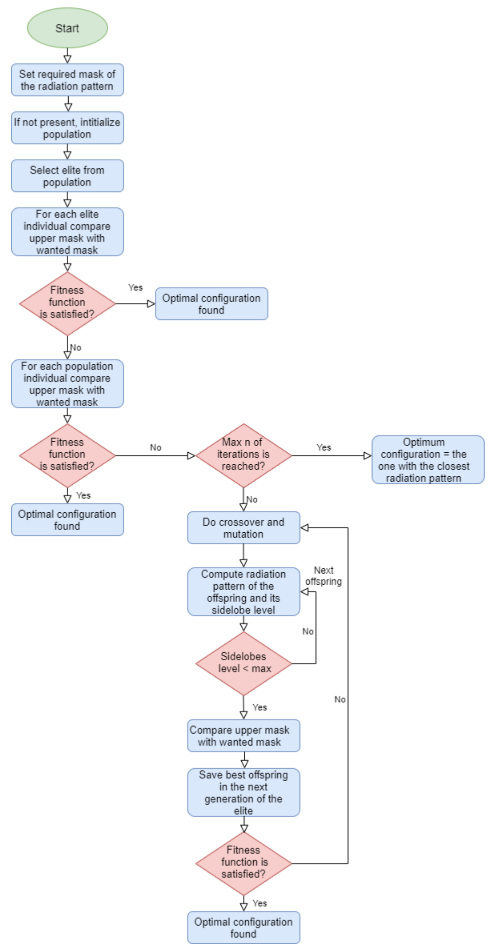

Fig. 4. Flow-chart of the adopted Genetic Algorithm.

upper mask is given in input to the algorithm. The algorithm starts from the *population*, that contains some of the possible phase configurations required by the environment and their corresponding radiation patterns and upper masks. It may include more coding matrices that provide the same or "enough" similar radiation pattern. This information may be repetitive, so another set is created where only the coding matrices, and their related information, that give a "quite" different radiation pattern are included. This set is called *elite*.

The *fitness function* consists in checking that the computed radiation pattern from the considered individual is "enough" similar to the wanted radiation pattern. More precisely, this means that the main beams should have the same directions and in checking that the sidelobes level of the individual in question is lower than a certain threshold. In order to evaluate how much the direction of the main beam is distant from the wanted one, parameter δ is adopted. It is evaluated as the distance between the exact central location of the main beam in the radiation pattern given in input and the one in the radiation pattern corresponding to the coding matrix in output. To have a more precise evaluation of the distance, the position of the two beams has been computed in spherical coordinates. So, the parameter δ has been evaluated in terms of difference of angles in azimuth (ϕ) and elevation (θ):

$$\delta_\theta = |\theta_w - \theta_o| \tag{1}$$

$$\delta_\phi = |\phi_w - \phi_o| \tag{2}$$

where the subscript *p* indicated the predicted angle, while *e* the expected angle. If the two deltas are lower than a fixed accuracy value, then the phase configuration that generates that radiation pattern corresponds to the searched one. So, the fitness function is represented by the following equations:

$$\delta_\theta \leq \epsilon_\theta \tag{3}$$

$$\delta_\phi \leq \epsilon_\phi \tag{4}$$

where ϵ_θ and ϵ_ϕ are small values in degrees chosen according to the accuracy required by the system.

The radiation pattern generated by the considered metasurface with a certain phase configuration and with orthogonal illumination is derived by the total reflected electric field, whose formula is shown in eq. 5. The x-,y- and z- components of the electric field are derived from it.

$$E_{\text{tot}} = \sum_{ii=1}^{m} \sum_{jj=1}^{n} \|\Gamma_{ii,jj}\| e^{i<\Gamma_{ii,jj} + i\,k\,d\,\xi_{ii,jj}} \tag{5}$$

$$with \quad \xi_{\text{ii,jj}} = ((ii - \frac{1}{2})\cos(pp) + (jj - \frac{1}{2})\sin(pp))\sin(tt) \tag{6}$$

where m and n are the number of meta-atoms in the two dimensions, Γ is the reflection coefficient, *k* is the wavelength number and *d* is the distance among two adiacent meta-atoms. *tt* and *pp* are two matrices made by the copy of two vectors θ and ϕ respectively in each row and in each column. More specifically, θ is a vector made by 100 equi-spaced values between 0 and $\frac{\pi}{2}$, while ϕ is made of the same number of values between 0 and 2π. The values of Γ are the ones evaluated for the meta-atom during the simulation.

When the environmental conditions require that the impinging signal on the meta-surface is steered of a different angle (in both azimuth and elevation angles), the algorithm searches the new matrix of reflective phases of the meta-atoms in the *elite*. If none of the individuals inside the *elite* can satisfy the *fitness function* (none can produce the wanted radiation pattern), the solution is searched inside the *population*. If it is not present neither there, the offspring of the *elite* is generated by adopting operations of *crossover* and *mutation* and their radiation patterns are computed. If the sidelobe level is lower than the maximum, the *upper mask* of the radiation pattern of the offspring is generated and compared to the *upper mask* of the required radiation pattern. In the meanwhile, the best offspring are saved in the next generation of the *elite*. If the fitness function is satisfied by one of the offspring, the optimal configuration is found; otherwise, the last-discussed procedure is repeated with the updated version of the *elite*. If the maximum number of iterations is reached and no optimum configuration is found, the best phase configuration is chosen among the ones in the *population* and the ones lastly-generated through the *crossover* and *mutation*.

Some examples of coding matrices obtained in output to the algorithm according to the given input are shown in Figs. 5 and 6. The first figure shows the case of a wanted radiation pattern where the main beam has ϕ= 0°. As it is possible to notice from the figure, the coding matrix obtained by the algorithm allows to generate a quite similar radiation pattern, with the same position of the main lobe, but with higher sidelobes. A similar behaviour happens in the second case, where a radiation pattern with main beam at ϕ= 135° is considered. Also in this case, the radiation pattern obtained from the calculated coding matrix has the same position of the main lobe but higher sidelobes. However, in all the cases the level of the sidelobes is acceptable. In the shown coding matrices the yellow corresponds to a reflective phase of 180°, while the blu to 0°.

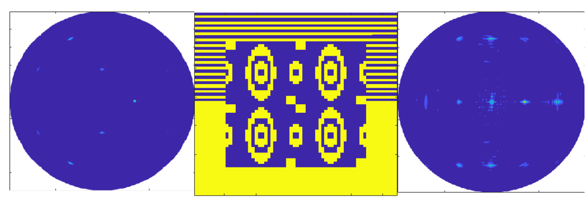

Fig. 5. Example of input and corresponding output to the algorithm: wanted radiation pattern with ϕ=0° (1st image); obtained coding matrix in output (2nd image) and radiation pattern corresponding to that coding matrix (3rd image).

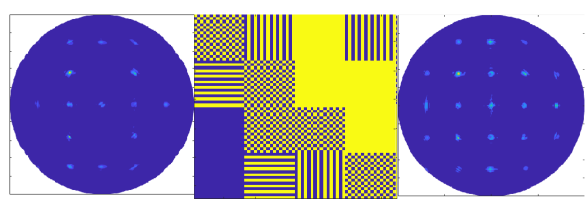

Fig. 6. Example of input and corresponding output to the algorithm: wanted radiation pattern with ϕ=135° (1st image); obtained coding matrix in output (2nd image) and radiation pattern corresponding to that coding matrix (3rd image).

IV. Performance evaluation

In this section, we first assess the quality of our proposed GA approach and then, we evaluate its performance from a communication point of view.

TABLE I
SIMULATION RESULTS

	μ	σ	MoE_{95}	min_{95}	max_{95}	MoE_{99}	min_{99}	max_{99}
$\delta\ \theta$	5.68	3.03	1.19	4.49	6.87	1.57	4.12	7.25
$\delta\ \phi$	15.81	23.73	9.3	6.51	25.11	12.25	3.56	28.06
$t_{conv_{train}}$ [s]	136.14	126.18	49.46	86.68	185.6	65.11	71.03	201.25
t_{conv} [s]	2.24	0.08	0.03	2.21	2.28	0.04	2.2	2.29

TABLE II
CONFUSION MATRIX

Exp. w	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13
w1	1	0	0	0	0	0	0	0	0	0	0	0	0
w2	0	0	1	0	0	0	0	0	0	0	0	0	0
w3	0	0	1	0	0	0	0	0	0	0	0	0	0
w4	0	0	0	1	0	0	0	0	0	0	0	0	0
w5	0	0	0	0	1	0	0	0	0	0	0	0	0
w6	0	0	0	0	0	1	0	0	0	0	0	0	0
w7	0	0	0	0	0	0	1	0	0	0	0	0	0
w8	0	0	0	0	0	0	0	0	1	0	0	0	0
w9	0	0	0	0	0	0	0	0	1	0	0	0	0
w10	0	0	0	0	0	0	0	0	0	1	0	0	0
w11	0	0	0	0	0	0	0	0	0	0	0	1	0
w12	0	0	0	0	0	0	0	0	0	0	0	1	0
w13	0	0	0	0	0	0	0	0	0	0	0	0	1

A. Accuracy Evaluation of the Genetic Algorithm

In order to demonstrate the effectiveness and evaluate the accuracy of the proposed algorithm, we have selected some specific parameters to be evaluated. The accuracy of the main beam localization in the radiation pattern obtained from the resulting coding matrix can be described by the parameters δ, more specifically δ_θ and δ_ϕ, which are defined in the previous Section. These parameters have been evaluated and averaged on 25 simulations using different radiation patterns in input to the algorithm. Also the standard deviation σ has been computed together with the margin of errors at 95% and 99%. The obtained values are shown in Table I. δ mean values are not very small because they consider also the cases when the algorithm cannot find the wanted angles and returns the configuration with the nearest angles. However in many situations this variation of the angles from the wanted ones is not worthy. Also the time of convergence of the algorithm is taken into account in the same table. Its mean value during the training phase of the algorithm is of the order of hundreds of seconds because it accounts the time needed by the algorithm to find a new configuration. But after the training step, the convergence time reduces to 2 seconds, that is suitable for real-time scenarios.

In order to evaluate the accuracy of the adopted Genetic Algorithm, the confusion matrix has been evaluated in Table II. A confusion matrix is a technique to check the performances of a classification algorithm. It allows to have a better idea of when the algorithm fails and of which errors it makes [15]. In the considered case, the confusion matrix has been computed on different directions of the main beam. More specifically the matrix shows how many times expected angles of the main beam coincide with the predicted ones by the algorithm and how many times the algorithm provides the incorrect angle. The rows contain the expected angles of the main beam, while the columns the predicted ones. From the confusion matrix, the accuracy of the algorithm can be derived. It is computed as the ratio between the number of correct predictions (the numbers in the main diagonal of the matrix) and the total predictions made :

$$accuracy_{\%} = \frac{\sum_{i=1,j=1}^{m,n} CM(i,j)}{\sum_{i=1}^{m}\sum_{j=1}^{n} CM(i,j)} \cdot 100 \tag{7}$$

where CM is the confusion matrix and i, j indicate respectively the rows and the columns. By using this formula, the obtained accuracy is 76.9%.

TABLE III
SIMULATION PARAMETERS

$P_{reflected}$	$0.81\times$ EIRP
f	78.52 GHz
B	175 MHz
NF	6
W	10
t	1 s
v	25 km/h
β	10

B. Communication Performance

In this section we evaluate the communication performance for the considered scenario, in which our reconfigurable meta-surface is used to track a mobile receiver. The communication channel is assumed to be in free space. The adopted parameters are listed in Table III. The reflected power for the specific meta-surface configuration has been calculated and is 81 % of the power transmitted by the RSU (namely the maximum power that can be transmitted, the European EIRP - Effective Isotropic Radiated Power, 57 dBm). The working frequency and bandwidth are the ones in which the meta-surface performs beam-steering, namely 78.52 GHz and 175 MHz, respectively.

Firstly, the outage probability is computed [16]. It is defined as the instantaneous information rate that falls below a certain threshold β :

$$Pr_{outage}[SNR < \beta] = 1 - e^{-\beta d^n \frac{P_{noise}}{P_{rx}}} \tag{8}$$

where *SNR* is the signal-to-noise ratio, β the threshold, *d* the distance of the receiver, *n* is the path loss exponent. The noise power, P_{noise} represents the thermal noise given a certain Noise Figure. The received power is computed as following :

$$P_{rx} = K_i \frac{\pi^2}{bw^2} \frac{1}{((vt)^2 + d^2)^{n/2}} \tag{9}$$

with :

$$K_{idB} = P_{tx} - W + 10\, n\, \log_{10}\left(\frac{\lambda}{4\pi d}\right) \tag{10}$$

where *bw* stands for beamwidth, *v* for vehicle speed, *d* for distance of the receiver from the RSU, P_{tx} is the transmitted power by the meta-surface and *W* is the shadowing margin. Fig. 7 shows the behaviour of the outage probability wrt. the distance in case of adoption of our reconfigurable meta-surface and without it. As it is possible to notice, without the use of the meta-surface the outage probability reaches the maximum value around 3 meters of distance from the receiver; with

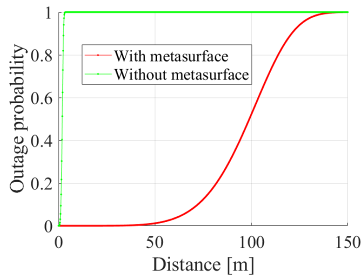

Fig. 7. Outage probability evaluated wrt. the distance of the receiver in presence of the discussed meta-surface and without meta-surface.

the adoption of the meta-surface, it is possible to reach very further distances, since the maximum is reached around 140 meters. From the outage probability, the channel capacity is evaluated. It is defined as the throughput of success delivery with constrained outage probability:

$$C = (1 - Pr_{outage})\, R \tag{11}$$

where *R* is the instantaneous rate:

$$R = B\, \log_2(1 + SNR) \tag{12}$$

that depends on the working bandwidth *B* and on the *SNR*. In Fig. 8, the capacity trend is shown with respect to the distance of the receiver. It is worth to notice that the capacity

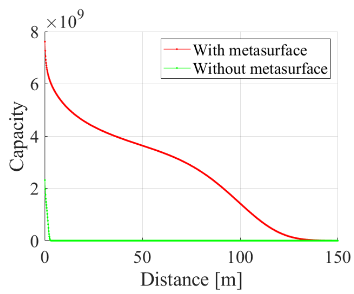

Fig. 8. Channel capacity evaluated wrt. the distance of the receiver in presence of the discussed meta-surface and without meta-surface.

has a similar behaviour to the outage probability: in case of no meta-surface, the capacity falls to 0 around 3 meters of distance; instead, by adopting the meta-surface, it reaches 0 around 140 meters. Moreover, in this case, for very low distances, the capacity is about four times higher than the case with no meta-surface.

V. Conclusion

In this paper, the real-time beam-steering based on a specific reconfigurable meta-surface operating at mmWaves is investigated. The behaviour of the adopted meta-surface unit-cell is discussed and its suitability for the intended aim is demonstrated. Then, a specific Genetic Algorithm to control the reconfiguration of the meta-surface is adopted, given the desired direction of steering in input. Great attention is paid to the fitness function, related to the radiation pattern, and to the two operators of this algorithm, cross-over and mutation. The performance of the adopted GA are evaluated. Specifically, the convergence time and the accuracy of the main beam localization of the resulting radiation pattern are evaluated. Finally, the communication performance are discussed through the computation of the outage probability and the channel capacity. Results obtained demonstrate the effectiveness of this approach and the validity of the parameters selected to perform the beam steering functionality. Even though the evaluation has been realized and demonstrated for a specific configuration, the approach is generally applicable to other meta-surface configurations with the same functionalities. In future, we aim to investigate the performance of the approach in presence of other interfering transmitters.

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